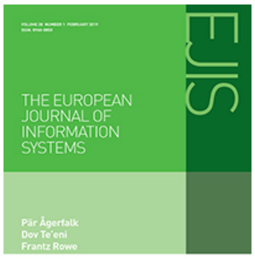

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Digital M&A, digital innovation, and firm performance: an empirical investigation

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ABSTRACT

Aiming to support digital innovation endeavours, industrial-age companies increasingly acquire firms that heavily build upon digital technologies. Related research has raised serious concerns regarding the prospects of such plans, yet has not focused the particular context of digital mergers and acquisitions (M&A). Drawing on a knowledge-based perspective as well as the particularities of digital technologies and the context of digital innovation, we theorise the link between digital M&A, a digital knowledge base on the part of the acquirer, and the consequences for digital innovation and firm performance. We employ panel data regressions to a longitudinal dataset of the world's largest automobile manufacturers. Our findings suggest that executing digital M&A contributes to building the digital knowledge base of industrial-age firms, which in turn enables them to drive digital innovation. Our findings further indicate that digital innovation improves firm performance of industrial-age firms. We discuss implications for information systems research about M&A and digital innovation as well as recommendations for managerial practice.

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Mergers and acquisitions; digital innovation; digital knowledge base; automotive industry; panel data regression

1. Introduction

Even in industrial-age industries, companies need to engage in digital innovation, that is, the creation of or change in market offerings that result from the use of digital technologies (Nambisan et al., 2017), as failure to do so risks losing customer bases and market positions to new digital competitors (Gregory et al., 2018). When targeting digital innovation, industrial-age incumbents need to combine digital and physical components for new value creation (Yoo et al., 2010). Building a digital knowledge base to enrich their established knowledge might therefore be a viable, yet also challenging strategy given the capability gaps industrial-age incumbents encounter in digital innovation (Svahn et al., 2017). While these firms can choose from among various options to build a digital knowledge base, such as internal experimentation or forming joint ventures and strategic alliances (Kogut & Zander, 1992), business press highlights that industrial-age incumbents increasingly turn to mergers and acquisitions (M&A) to support these endeavours (Boote et al., 2019; Malette & Goddard, 2018).

Contrary to these efforts in business practice, prior literature raises serious doubts regarding the potential gains for the industrial-age incumbent's innovativeness that can be expected from such M&A (e.g., Cloodt et al., 2006). If a target's knowledge base is too distant from that of the acquirer, profiting from the acquired knowledge is particularly challenging (Ahuja & Katila, 2001; Gao & Iyer, 2006; Makri et al., 2010). Nevertheless, digital M&A, that is, acquisitions of (or mergers with) firms that intensely leverage digital technologies (Bharadwaj et al., 2013) as critical elements of their business model (Huang et al., 2017; Tumbas et al., 2017), may differ from other transactions given the specifics of digital technologies and the context of digital innovation. In particular, the inherently dynamic and malleable nature of digital technologies (Y. Yoo et al., 2012) might drive post-M&A knowledge combinations and thus lead to digital knowledge creation and digital innovation (Y. Yoo et al., 2010). To date, however, it is unclear if digital M&A help incumbents to close capability gaps and drive their digital innovation capabilities.

Past information systems (IS) research has generated valuable insights with regard to M&A (e.g., Benitez et al., 2018). However, prior work has mainly investigated contexts in which IS are viewed primarily as a byproduct, not the target, of M&A, thereby ascribing an instrumental value to IS (Yoo, 2010). More recently, research has focused on the acquisitions of IT firms to build technical knowledge for innovative purposes in which IS are central to the rationale of the acquirer – thus rendering a different emphasis, ascribing an inherent value to IS (Yoo, 2010) and focusing knowledge-based perspectives, relevant (e.g., Henningsson et al., 2016). While this latter stream of inquiry is particularly germane to digital

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innovation, it has focused only on digital contexts and industries (e.g., Datta & Roumani, 2015). Although substantially different in nature (Y. Yoo et al., 2010) and highly relevant in practice (Boote et al., 2019), digital M&A and digital innovation by industrial-age incumbents remain unexplored.

Therefore, drawing on a knowledge-based perspective, our study investigates the link between digital M&A, the digital knowledge base of the acquirer, and the impact on digital innovation in industrial-age contexts. Furthermore, we examine the impact of digital innovation on firm performance. We employ panel data regressions based on a longitudinal dataset of the automotive industry from 2000 to 2016. The automotive industry is particularly interesting, as it represents a class of contexts that is characterised by industrial heritage and products but simultaneously embraces digital innovation (Svahn et al., 2017). Our findings suggest that executing digital M&A contributes to building the digital knowledge base of industrial-age firms, which in turn enables them to drive digital innovation leading to increased firm performance. Furthermore, we find a positive effect of digital M&A on digital innovation, which is partially mediated by new digital patents filed by the acquirer. Thus, digital M&A positively influence digital innovation by helping to build the digital knowledge base of the acquirer.

Our study contributes to research on IS in M&A (e.g., Hedman & Sarker, 2015). We complement work on M&A for the inherent value of IS, which to date has only focused purely digital settings (e.g., Datta & Roumani, 2015), with an emphasis on industrial-age contexts and derive implications building upon the unique traits of digital M&A (as compared to other acquisitions) and the context of digital innovation in knowledge creation and application. Furthermore, as a second contribution, we add to research of digital innovation (Nambisan et al., 2017). We extend work, which has progressed in conceptualising digital innovation (e.g., Y. Yoo et al., 2010) and revealing tensions and challenges faced by industrial-age incumbents (e.g., Svahn et al., 2017), by providing insights into how these incumbents can create and convert digital knowledge into new digital products and services as well as how this process affects firm performance.

2. Background

2.1. Information systems in mergers & acquisitions

Driven by the observation that a substantial part of the success of M&A hinges on IS integration between acquirer and target, in the past decade, IS research related to M&A has proliferated (e.g., Henningsson & Kettinger, 2016). This research has generated valuable insights about a large variety of antecedents, strategies, and approaches of IS integration and has related them to synergy realisation in M&A (e.g., Benitez et al., 2018). Importantly, such synergies might result from the ex-ante planned integration of the existing IT assets of acquirer and target but might also include novel, unexpected discoveries (Busquets, 2015). At the same time, the relation of M&A and IS in business practice has diversified substantially (Malette & Goddard, 2018), a phenomenon echoed by recent reviews and editorial comments emphasising the need for contextual differentiation (Hedman & Sarker, 2015; Henningsson et al., 2018).

Indeed, two broad contextual streams can be discerned that differ in how they relate to IS's role regarding M&A by implicitly or explicitly ascribing either *instrumental* or *inherent* value to IS (Yoo, 2010). This differentiation is important, as it not only demarcates distinct motivations behind M&A but each stream also casts IS integration in a different light. Studies in the first stream, representing the majority in IS M&A research, focus on contexts where IS are not part of the acquirer's rationale for M&A but are seen as instrumentally valuable by *influencing* or *enabling* the M&A process and IS integration is often related to realising "cost-based synergies by consolidating IT infrastructures" (Benitez et al., 2018, p. 39). Recently, however, companies across industries have conducted M&A with the primary goal of accessing new IS capabilities as part of their agenda to create and market new digital products and services (Malette & Goddard, 2018). Accordingly, a second research stream has emerged that focuses on contexts where the acquisition of IS is the main driver behind the M&A decision and the inherent value of IS is precisely what *initiates* or *triggers* M&A. As, in these contexts, acquirers aim to add the target's IS capabilities to its own (Wang & Hui, 2017) and as integration might also damage the unique capabilities of the target (Henningsson et al., 2016), IS integration needs be conducted cautiously and with a different focus (Datta & Roumani, 2015). By engaging in these types of M&A, companies see a chance "of acquiring knowledge to build intellectual capital and launch innovative solutions" (Datta & Roumani, 2015, p. 202). Accordingly, knowledge exchange between the target and acquirer (e.g., Tanriverdi & Uysal, 2011) is a key goal of IS integration to unlock revenue-based synergies (Benitez et al., 2018), rendering knowledge-based perspectives particularly relevant. For instance, Kathuria et al. (2011) pointed to the importance of retaining and transferring technical IT knowledge of the target for the success of M&A. While Henningsson (2015) employed a knowledge-based perspective to investigate learning effects from multiple acquisitions on the part of acquirers, this view rather pertains to the instrumental perspective by focusing on the building of *organisational M&A knowledge* about IS integration, or "learning to acquire." As indicated by Y. Yoo et al. (2007), contextual differences in M&A render different knowledge-sharing needs relevant. Therefore, besides the value of the study by Henningsson (2015) in pointing to the importance of knowledge-building from acquisitions, complementary perspectives that focus on the building of *technical knowledge*, or "acquiring to learn" (Vermeulen & Barkema, 2001), are particularly relevant in the context of digital innovation.

Understandably, IS research in the stream focused on inherent IS value has selected mainly digital industry settings (such as internet or software markets) (e.g., Dowie et al., 2017; Gao & Iyer, 2006). In these contexts, acquisitions that complement existing knowledge bases by delivering innovative components that can be quickly related to pre-existing digital products, services, and installed bases have been found to drive the innovation performance of the acquirer (Datta & Roumani, 2015). Apart from that, studies that employ a knowledge-based perspective on M&A and innovation are rare in IS research.

In the management domain, valuable insights have been generated in this regard (e.g., Cloodt et al., 2006). Summarising the state of research, McCarthy and Aalbers (2016) described that knowledge-related M&A conceptually make sense for the acquirer yet, on average, empirically yield disappointing results. As a key insight, technological knowledge obtained from M&A, although potentially delivering creative new inputs to the acquirer (Ahuja & Katila, 2001), is often highly contextualised and hard to transfer (Ranft & Lord, 2002). Research has found that when a moderate overlap exists between the knowledge bases of an acquirer and a target, there can be a positive effect, while other constellations are likely to yield negative results. In particular, knowledge that is too close to that of the acquirer might not provide enough novelty and knowledge that is too distant might be too challenging for the acquirer to utilise (Makri et al., 2010). So far, however, management research has refrained from investigating digital M&A. The applicability of analogies to and insights from other M&A are limited because of the unique characteristics of IT firms and the digital resources they build upon (Chang & Cho, 2017; Du, 2015; Gao & Iyer, 2006; Kallinikos et al., 2013).

In sum, studies that employed a knowledge-based perspective and attended to the peculiarities of digital M&A are scarce. Existing work either focused on non-digital M&A (e.g., Ahuja & Katila, 2001) or on digital M&A in purely digital contexts (Datta & Roumani, 2015). In times of digitalisation (Tilson et al., 2010), however, traditional firms from non-digital industries also increasingly seek to acquire IS capabilities through M&A (De Man & Duysters, 2005). An important difference to digital industries is that, owing to their non-digital heritage, these firms may not be able to directly assimilate and apply innovative digital knowledge via M&A, as it might be too distant (Gao & Iyer, 2006; Lyytinen et al., 2016). Furthermore, these firms need to constantly combine digital with physical knowledge for digital innovation (Y. Yoo et al., 2010), further driving post-M&A complexity. To date, we know very little about digital M&A conducted by industrial-age firms, especially regarding digital innovation by the acquirer.

2.2. Digital innovation and industrial-age incumbents

Prior research has shown how digital ventures successfully develop digital innovation (Huang et al., 2017). Much less is known about digital innovation by industrial-age incumbents. Existing research in this regard has pointed to the substantial challenges and concerns these firms experience when embracing digital innovation (Piccinini et al., 2015). Among the multiple challenges that industrial-age incumbents encounter, which include overcoming institutionalised thinking (Henfridsson & Yoo, 2014) as well as changing processes, structures or governance arrangements, capability concerns play a fundamental role (Svahn et al., 2017). Hurdles in this regard result from the peculiarities of digital innovation in industrial-age contexts. Here, digital innovation builds upon a layered modular product architecture (Y. Yoo et al., 2010). While physical products such as cars build upon a modular architecture whereby interlocking components are assembled into a single physical entity and all innovating parties share product-specific knowledge, the layered modular architecture comprises loosely coupled layers of devices, networks, services, and contents, each following a different functional design hierarchy in which knowledge is product-agnostic (Lusch & Nambisan, 2015; Y. Yoo et al., 2010). Accordingly, "[T]he semantic distance of knowledge elements necessary for product innovation grows" (Lyytinen et al., 2016, p. 56). For industrial-age incumbents, existing case studies illustrate that firms aim to close resulting capability gaps via internal measures (e.g., building new organisational units such as innovation hubs) and seek for external innovation partners (Svahn et al., 2017). However, besides occasional single case evidence, to date, we have no systematic, large-scale examination of the antecedents and consequences of particular approaches to closing capability gaps for digital innovation by industrial-age incumbents.

Prior work has described knowledge and learning as key issues in digital innovation that can drive or inhibit a firm's ability to digitally innovate (Kohli & Melville, 2018). This emphasis is understandable given the consequences of the modular layered architecture. The various components in the different layers are exchangeable, offering ample (re)combination possibilities (Henfridsson et al., 2018). Thus, digital innovations are intentionally incomplete and enduringly enable the development of new modules, a trait called "generativity." Thereby, digital innovations also merge a variety of traditional industry segments and use contexts (such as driving and entertainment), a trait called "convergence." As to these traits, new knowledge creation involving heterogeneous knowledge bases is a constant in digital innovation (Y. Yoo et al., 2012). However, while digital innovation has been described as building upon heterogeneous knowledge (Lyytinen et al., 2016), the consequences for knowledge bases of incumbent firms remain unclear. On the one hand, knowledge for digital innovation has been conceptually described as distributed across actors (Y. Yoo et al., 2012). On the other hand, it also is reported to be interwoven, increasingly inseparable (Y. Yoo et al., 2010), and questioning the fault lines between established knowledge domains (Y. Yoo et al., 2012). To date, the lingering question of where to locate knowledge creation and knowledge combination in digital innovation in industrial-age contexts remains unresolved.

3. Theoretical framework and hypotheses development

3.1. A knowledge-based view of digital M&A and digital innovation in industrial-age industries

The knowledge-based view of the firm provides an interesting lens through which to study both M&A and innovation by following the underlying assumption that "[P]roduct creativity is primarily a function of the firm's ability to manage, maintain, and create knowledge" (Zhou & Li, 2012, p. 1090). Two dialectically intertwined processes are central to this view: building knowledge bases and applying knowledge. The two processes are equally important as, under dynamic competition, the value of knowledge is subject to change (Spender, 1996). In the particular context of digital innovation, the central role of knowledge is underscored, as it is seen to "underlie digital business innovation capabilities, either as enabler or hindrance" (Kohli & Melville, 2018, p. 6).

Digital innovation in industrial contexts is about the combination of digital and physical components (Y. Yoo et al., 2010) and, thus, the knowledge underlying these components. While industrial-age incumbents possess profound knowledge with regard to the relevant physical components, they can choose between different options with regard to digital knowledge. On the one hand, they may decide to leave digital knowledge creation to suppliers or other third parties, such as digital ventures (Tumbas et al., 2017), and combine it with their established knowledge. Indeed, digital innovation has been described as distributed and combinatorial, involving a heterogeneous set of external actors (Y. Yoo et al., 2012). Moreover, the peculiarities of the layered modular architecture of digital innovation do not require every innovating party to possess the particular knowledge necessary in every single layer (Y. Yoo et al., 2010). On the other hand, physical players may consider building their own digital knowledge base for two reasons. First, from a strategic point of view, digital resources become a key differential factor in value creation and capture (Bharadwaj et al., 2013). Thus, in the context of digitalisation (Tilson et al., 2010), the value of digital knowledge increases, even for industrial-age incumbents, as it can provide an amplifying effect to the established competences of the incumbent (Spender, 1996). Leaving this important function to other actors can lead to dangerous dependencies (Lee & Berente, 2012) and also risks that competitors acquire and block access to valuable digital knowledge (Gao & Iyer, 2006). Second, from an architectural point of view, digital knowledge is important for industrial-age incumbents with regard to the overall set-up of new digital products or services, as

> in the wake of a major shift in a product's architecture, systems integrators need to develop internal capabilities in components to gain better understanding of the inner workings of the new components. They cannot rely solely on external suppliers to gain knowledge about new developments. (Lee & Berente, 2012, p. 1429)

Thus, to sustainably integrate their core offering within the layered modular architecture and provide ground for new digital products and services, building a digital knowledge base themselves seems promising for industrial-age incumbents (Lyytinen et al., 2016).

Industrial-age incumbents can engage in various strategies to create digital knowledge. First, they could try to develop the knowledge internally by reorganising, conducting experiments, or pursuing accidental discoveries (Kogut & Zander, 1992). Indeed, research has reported reorganisations that lead, for example, to extended responsibilities of the IT departments or the establishment of new units such as app development groups (Svahn et al., 2017). However, internal knowledge development is often path-dependent, time-consuming, and uncertain as to success, presenting a challenge when firms need to quickly develop knowledge rather distant to their existing knowledge base (Graebner et al., 2010). The context of digital innovation exerts temporal pressures, as customers increasingly expect new digital products and services (Huang et al., 2017). A second option is to obtain knowledge externally from three potential sources (Kogut & Zander, 1992). First, firms might hire digital human capital, even though "hiring new workers is not equivalent to changing the skills of a firm" (Kogut & Zander, 1992, p. 383). However, integrating new technical staff for innovative purposes might take considerable time (Lee & Allen, 1982). Second, firms might build strategic alliances or joint ventures, providing them access to new knowledge (Bos et al., 2017). However, access depends on the will of the respective partner. Furthermore, contract design might be complicated and time-consuming. Third, they might pursue M&A, through which firms gain the full right of disposal concerning new external knowledge in relatively short amounts of time (Datta & Roumani, 2015) and also avoid direct competitors gaining access to the digital knowledge of the identified targets (Gao & Iyer, 2006).

Drawing on this background, we combine theory with the peculiarities of digital technologies and digital innovation to derive our hypotheses. Table 1 defines our core concepts.

3.2. Building digital knowledge from digital M&A

Knowledge creation relies on (re)combination of knowledge (Bos et al., 2017). M&A provide firms access to new knowledge, expanding the set of potential, novel knowledge combinations (Vermeulen & Barkema, 2001). M&A can therefore positively influence the acquirer's development of new patents (Ahuja & Katila, 2001), which indicate an extension of a knowledge base as a result of learning (Lane et al., 2006). However, the ease of learning can vary with the characteristics of the knowledge acquired (Cohen & Levinthal, 1990). Indeed, a lack of positive outcomes from M&A for the acquirer is often associated with the nature of knowledge involved (Ranft & Lord, 2002), particularly its context specificity. Knowledge is often hard to separate from the contextual conditions of its development and past use (Andersen, 1999), thus affecting its transferability and reusability (Majchrzak et al., 2004). Accordingly, "[T]echnological acquisitions, in particular, are known to be prone to complication and disappointment" (McCarthy & Aalbers, 2016, p. 1818) and empirical evidence, in total, suggests a rather negative influence on the acquirer, especially when distant knowledge is involved (e.g., Cloodt et al., 2006; Makri et al., 2010). From this perspective, even if the acquirer decides to utilise and not foreclose the target's knowledge from the market, a potential alternative motivation (Shenoy, 2012), it is questionable if it can build knowledge from digital M&A.

Digital M&A, however, may differ from other M&A owing to the particular characteristics of digital technologies that are bought through the deal. Digital technologies are context-agnostic and not predetermined in their use (Henfridsson et al., 2018). More specifically, three particular characteristics set digital technologies apart from others (Y. Yoo et al., 2010). *Reprogrammability* – the continuous adaptability of digital technology – enables the separation of form and function. This characteristic allows for adaptations and thus might ease adjustments of newly acquired components to achieve a better fit with existing components of the acquirer. *Homogenisation of data* – independence from particular artefacts and infrastructures for storing, processing and transmission of data – enables the separation of content and medium. This characteristic might ease combination with a variety of existing components of the acquirer. Lastly, *self-reference* – the accumulation of digital technology – enables building on top of the existing base without possessing and understanding all necessary preceding competences. Components of the target might thus provide a base that invites the acquirer to develop new digital components. In other words, "The malleability (e.g., re-programmability), homogeneity (e.g., standardised software languages) and transferability (e.g., ease of transferring digital representations of any object) [are] at the heart of technologies meshing digital, and often physical materiality" (Hinings et al., 2018, p. 52).

In sum, even though acquisition targets might have applied their skills and assets to a very specific purpose, the characteristics of the digital technologies involved allow ample opportunities to reuse those components (Henfridsson et al., 2018). The knowledge embedded in the technologies (Datta & Roumani, 2015; Zander & Kogut, 1995) can thus spread across use-contexts or create new use-contexts (Fleming, 2001), consequently driving the potential for recombination and knowledge creation (Ahuja & Katila, 2001; Bos et al., 2017; Dong & Yang, 2019). Accordingly, we present the following hypothesis:

Table 1. Core concepts.

Concept	Definition
Digital Technologies	Digital technologies are defined as combinations of information, computing, communication, and connectivity technologies and include instances such as cloud computing, mobile technology, social media or big data analytics (Bharadwaj et al., 2013).
Digital M&A	Digital M&A are defined as acquiring of (or merging with) firms that intensely leverage digital technologies as critical elements of their business models (Tumbas et al., 2017, Huang et al., 2017).
Digital Knowledge Base	A digital knowledge base is defined "as the total articulated and tacit knowledge of an organization … leading to a set of capabilities [to leverage digital technologies] that enhance the chances for growth and survival" (Vermeulen & Barkema, 2001, p. 459).
Digital Innovations	Digital innovations are defined as creations of or changes in market offerings that result from the use of digital technologies (Nambisan et al., 2017).

Please note that Table A1 additionally describes how these concepts have been operationalised for our empirical investigation.

H1. *There is a positive relationship between digital M&A and new digital patents filed by the acquirer.*

3.3. Digital knowledge base and digital innovation

In general, "[M]arketable products and services are the end result[s] of successful application of value-creating knowledge" (Ranft & Lord, 2002, p. 422). Furthermore, the knowledge-based view posits that innovativeness is related to a firm's knowledge base (Ahuja & Katila, 2001). However, knowledge per se is not equal to innovation but needs to be converted into the creation of new or the change of existing market offerings. In digital innovation in industrial contexts, materialising knowledge into innovation is special. First, digital innovations regularly exhibit *convergence* (Lyytinen et al., 2016), requiring the combination of heterogeneous knowledge. Industrial-age incumbents need to combine and entangle physical and digital components (Y. Yoo et al., 2012, 2010). Having built digital knowledge should therefore increase the chances of success in this regard (Kohli & Melville, 2018).

However, second, digital innovations are also characterised by *generativity* (Y. Yoo et al., 2012). The infinite possible combinations along the loosely coupled layers of the layered modular architecture (Y. Yoo et al., 2010) give rise to continuing dynamics and an increasing inseparability of innovation processes and outcomes (Nambisan et al., 2017). Therefore, knowledge is combined only temporarily, and finding new combination possibilities becomes an enduring endeavour (Y. Yoo et al., 2012). The existing digital knowledge base of a firm not only enables the firm to directly apply and combine that knowledge but also increases the firm's receptivity to new external knowledge. Thus, having built a digital knowledge base itself enables an incumbent firm to absorb and utilise further external digital knowledge, thus driving the potential for digital innovation (Cohen & Levinthal, 1990).

Accordingly, we present the following hypothesis:

H2. *There is a positive relationship between digital patents filed and digital innovation.*

3.4. Direct and indirect effects of digital M&A on digital innovation

While digital M&A may foster the building of a digital knowledge base, a direct effect on digital innovation is also possible (Datta & Roumani, 2015). Digital products and services, in the context of industrial-age incumbents, build upon a *layered modular architecture*. This architecture, in contrast to integrative or modular architectures, permits combining components across different layers without possessing all the necessary knowledge from different layers within a single firm (Y. Yoo et al., 2010). Thus, acquired components – such as an app for a car-sharing service – can be loosely coupled without the need for deep integration inside a single organisational hierarchy.

Accordingly, we present the following hypothesis:

H3a. *There is a positive relationship between digital M&A and digital innovation.*

We have argued that digital M&A is associated with a digital knowledge base and that such a base is, in turn, associated with digital innovation. Thus, taken together, H1 and H2 suggest that digital patents filed by the acquirer mediate the effect of digital M&A on digital innovation. Indeed, as described above, digital M&A might help industrial-age incumbents to develop digital innovations by cultivating a digital knowledge base as a platform for digital innovation (Kogut & Zander, 1992; Y. Yoo et al., 2012).

Accordingly, we present the following hypothesis:

H3b. *The relationship between digital M&A and digital innovation is partially mediated by new digital patents filed by the acquirer.*

3.5. Performance implications of digital innovation

In the digital age, customers increasingly expect offerings, even from traditional players, to pertain to their digitalised everyday life (Gregory et al., 2018; Yoo, 2010). Initial research, for example, concerning GM's OnStar service (Yoo, 2010), has indicated that digital innovation can successfully retain an industrial incumbent's core offering's attractiveness in the digital age, thus securing revenue streams for the physical device, and can also create new revenue sources aside from device sales through the other layers of the layered modular architecture. Here, as in the case of OnStar, customers might pay direct subscriptions for digital services in their car, and automakers might offer a platform through which third parties can market apps to car drivers and profit from revenue-sharing with these external partners.

Accordingly, we propose the following hypothesis:

H4. *There is a positive relationship between digital innovation and firm performance.*

4. Methodological approach

4.1. Sample

We focus on a longitudinal panel of automotive manufacturers from 2000 to 2016. As innovation processes differ greatly across industries, we focused on a single industry similar to prior research on innovation (Ahuja & Katila, 2001; Prabhu et al., 2005). The automotive industry provides us with a setting where digitalisation places all industry incumbents under strong pressure (Lee & Berente, 2012; Svahn et al., 2017). Owing to this pressure, all automotive manufacturers should aim for digital innovation, while the strategies to achieve this goal may differ from one incumbent to another. We selected the 30 largest automotive manufacturers by motor vehicle production rate in our starting year, 2000 (OICA, 2001). Companies could exit the sample by delisting or dissolving, but no new companies were allowed to enter. From the resulting sample, we included only original equipment manufacturers (OEMs) with available information on firms' acquisition activities as well as all other financial and informational data for regressions. The final sample comprised 23 OEMs that account for 332 firm-year observations.

4.2. Measures

In what follows, we describe our main variables and then focus on our control variables. Appendix A1 provides an overview of all variables used, their data sources, and their definitions.

4.2.1. Digital patents

We defined digital patents as patents that intensely leverage digital technologies (see Table A1). We drew patent information from the Espacenet database of the European Patent Office (EPO) because it included a worldwide collection of patent applications from various countries (Oltra & Saint, 2009). To identify digital patents, we followed a two-step approach.

First, we extracted all potential digital patents by performing a keyword search. Since each OEM files potentially thousands of patents in a single year, a manual evaluation of every patent was not feasible. Through the keyword search, we selected all patents that mentioned one of the keywords in its patent description or title. Building upon but advancing the approach of prior research (Hanelt et al., 2015), we started our keyword search using the broader search term "digital" and then also searched for the most significant digital technology trends, such as "cloud computing," "social media," "mobile technology," and "big data" (Bharadwaj et al., 2013). We manually screened and discussed the first search results to judge whether to expand or exclude search words. This process had two key effects. First, it confirmed our initial assumption that a keyword search was a useful preselection step for our variable coding, as we received several results that indeed contained respective keywords but focused on unsought aspects. Second, the screening revealed further keywords relating to subcategories of the technologies as well as synonyms, which we added to our keyword list. We performed a few test runs and reviewed the results to ensure a comprehensive coverage of potentially relevant patents. We then extracted all the patents of our OEMs for the years 1997 to 2016 that mentioned one of our keywords.

Second, three independent researchers carefully evaluated the patent information of each digital patent candidate. To ensure that they shared a common understanding, the coders started by evaluating a subset of data records in our sample. We selected patents from different years because digital trends changed vastly within our study's timeframe. After this introduction, the researchers started the final coding of partly overlapping samples. For example, the patent US9231998 USDB2 filed by Ford was determined a digital patent owing to its description in Espacenet, which said that the

> invention provides a computation management system for supervising and implementing computation-related tasks using cloud resources, in a manner that efficiently meets the demands of real-time communication between in-vehicle networks and the cloud server. (Espacenet, 2015)

After the three independent coders completed their classification, we compared the coherence of the coding. The inter-rater reliability (Cohen's kappa) indicated a substantial agreement of the coding (0.86). We discussed controversial cases until we reached a consensus on the allocation.

On the basis of the coding, we constructed two variables. We used the filing dates of the patent applications to assign the patents to particular years. This approach was important, as it ensured that we estimated the impact of digital M&A on new digital patent applications filed after the transactions. For H1, we used digital patents as the dependent variable, and we decided to create a variable that considered digital patent applications filed by an OEM in the current and subsequent two years (*3fy digital patents*). Consistent with previous research (Balsmeier et al., 2017; Custódio et al., 2019; Saldanha et al., 2017), we calculated the variables as the natural logarithm of one plus the number patent applications in the given and subsequent two years and also considered the pure count for robustness. As we also used digital patents as an independent (mediator) variable explaining digital innovations (H2–H3), we calculated a second variable (*3ly digital patents)* that captured digital patent applications in the three most recent years because we expected more than just immediate effects of digital patents on digital innovations. We further used again the natural logarithm of one plus the number of digital patents in the three most recent years.

4.2.2. Digital innovation

Digital innovation is defined as the creation of new market offerings or changes in them that result from the use of digital technologies (see Table A1). Based on this definition, we also considered new or changed market offerings based on digital technologies that were developed in combination with other actors (e.g., suppliers). To identify digital innovation by OEMs, we searched through the commonly used LexisNexis database (e.g., Dehning et al., 2003) and relied on the same two-step approach as for the variable digital patents.

First, we extracted all potentially relevant press releases between 2000 and 2016 by performing a keyword search following the same procedure as for the digital patents. As in prior research (e.g., Dewan & Ren, 2007), the search process on LexisNexis encompassed press releases in PR Newswire and Business Wire. Second, we assigned three independent researchers to investigate partly overlapping samples of the extracted press releases to evaluate whether they indeed referred to new or changed market offerings based on digital technologies. As an example of such an innovation, in 2015, Volkswagen (VW) announced the market introduction of its new connected car platform, Car-Net:

> Under the VW Car-Net connected vehicle services umbrella, features are divided into three key areas, each offering a unique set of customer benefits – "Security & Service" includes connected car services and advanced telematics, "Guide & Inform" enhances the navigation and advanced infotainment systems, and "App-Connect" provides seamless smartphone integration through three interfaces: Apple CarPlay®, Android Auto™, and MirrorLink®. (Volkswagen, 2015)

After the final coding, we compared the resulting lists, which again exhibited strong agreement (Cohen's kappa of 0.92). We discussed controversial cases to reach a decision. On the basis of the coding, we constructed a variable for the number of new or changed market offerings based on digital technologies reported by an OEM in the current and subsequent two years (*3fy digital innovation*). We applied a natural log transformation of the variable as well as the pure count in our analyses.

4.2.3. Digital mergers & acquisitions

We define digital M&A as acquisitions of (or mergers with) digital target firms, which we classify as firms that intensely leverage digital technologies as critical elements of their business models (see Table A1). To search for M&A that matched this definition, we first extracted all completed M&A transactions by OEMs between 1995 and 2013 from the commonly used SDC databank (Makri et al., 2010). We used a wider timeframe for the coding of our variable to allow testing of various lead–lag specifications. To decode digital M&A, we assigned three independent researchers to carefully analyse and evaluate overlapping samples of the OEMs' M&A. We required the researchers to elaborate on the targets' business descriptions as disclosed in SDC to determine whether they leverage digital technologies as critical elements of their business models. Moreover, we required the gathering of additional information from corporate websites, press articles, or press releases when the descriptions provided by SDC were imprecise. For example, for the 2013 acquisition by Ford of the target Myine Electronics Inc., a music solutions provider, further information sources were consulted that revealed that the company provides

> Livio Connect API, a middleware framework protocol that enables hardware to connect to and interact with various mobile phone applications. (Crunchbase, 2019)

Accordingly, the deal was determined a digital M&A. After the three independent researchers completed their classifications, partly overlapping subsamples were compared to assess the inter-rater reliability (Cohen's kappa of 0.89). We discussed the remaining controversial cases until we reached a consensus. On the basis of the coding, we constructed a variable that accounts for more than the immediate effects of digital M&A on an OEM's digital knowledge base. Specifically, we used a variable that covers the OEM's activity in digital M&A over the three most recent years (i.e., current and prior two years). Hence, we calculated the variable *3ly digital M&A* as the natural logarithm of one plus the number of digital M&A conducted in the three most recent years.

4.2.4. Firm performance

To investigate whether digital innovation drives firm performance, we examined both operating and capital market performance. To measure operating performance, we followed several studies by calculating the OEM's *return on assets* (e.g., He & Huang, 2011). We further measured OEMs' capital market performance by using the OEMs' *market-to-book ratio* (e.g., Uotila et al., 2009). Finally, we triangulated our analysis by using analysts' earnings per share (EPS) forecasts. While EPS is a proxy for a company's operating performance relative to one share of common stock, EPS analyst forecasts provide future performance expectations by well-informed capital market intermediaries. Specifically, financial analysts specialise in specific industries (e.g., Kadan et al., 2012) and are thus able to provide a forecast based on automotive and financial expertise. In detail, we used the *3-year EPS forecasts* provided by the IBES databank.

4.2.5. Control variables

Our first three hypotheses were directed at digital patents and digital innovation. As no prior studies have focused on similar proxies related to digital innovation, we started by selecting controls commonly applied in empirical innovation studies (e.g., Ahuja & Katila, 2001; Balsmeier et al., 2017; Custódio et al., 2019; Galasso & Simcoe, 2011; Saldanha et al., 2017). We included the OEMs' *size* since larger firms may have more resources for innovation purposes and *leverage* to control for financial constraints (Balsmeier et al., 2017). We included *R&D intensity* to control for internal innovation activities (e.g., Ahuja & Katila, 2001; Galasso & Simcoe, 2011) and the level of capital expenditures (*capex*) as the binding of internal resources could negatively affect digital innovation (e.g., Balsmeier et al., 2017). We considered the growth ability that may be positively associated with innovativeness by including *sales growth* (e.g., Custódio et al., 2019), and *capital intensity*, a measure used in innovation studies to control for manufacturing intensity (e.g., Custódio et al., 2019; Galasso & Simcoe, 2011). We included *diversification*, as it could help in innovation processes owing to a broader internal knowledge but also hamper control of the innovation process and thus negatively affect its outcome (Katila & Ahuja, 2002). As profitability-related proxies are frequently used in innovation studies (e.g., Saldanha et al., 2017) we further considered the OEM's *profit margin*. In addition to that, we included four controls specifically related to our research setting focused on digital M&A and innovation: (1) activities in *digital alliances*, since firms simultaneously engage in digital alliances when conducting digital M&As; (2) the OEMs' non-digital *M&A experiences*, since M&A integration skills could help OEMs translate digital M&As into future digital innovation; (3) the firm's *liquidity*, which could help to finance external innovation strategies such as M&A; and (4) *industry growth* to control for the possibility that digital innovations are timed with superior industry development. To investigate the impact of digital innovation on firm performance, we also used *diversification, profit margin, capex, R&D intensity, leverage, capital intensity, industry growth, size*, and *sales growth* as control variables. Finally, we included dummy variables for time effects in all our regression models and lagged each of the control variables by one year. Table A2 in Appendix A1 displays more detailed information on the calculation and data sources of all the control variables.

4.2.6. Model specifications

4.2.6.1. Analysing the relation between digital M&A, digital patents, and digital innovation (H1–H3).

In investigating H1–H3, we addressed several potential sources of endogeneity. First, a firm deciding to engage in digital M&A and to build up digital knowledge (i.e., to file digital patents) is likely to differ systemically from other firms. While we could account for some of these differences with our control variables, unobserved differences could remain. To address this issue, we exploited our panel dataset by estimating a firm fixed effects regression. While a negative binomial regression would be suitable for our (overdispersed) count variables, we opted, similar to prior research (e.g., Balsmeier et al., 2017; Custódio et al., 2019; Galasso & Simcoe, 2011), for an OLS firm fixed effects regression to estimate the natural log transformation of our count variables, digital innovation and digital patents. We did so as fixed effects negative binomial regressions come with several downsides. Specifically, they drop all observations without changes in the dependent variable, potentially causing selection bias (Shi et al., 2019), and they have been criticised for not providing a true fixed effects analysis (Allison & Waterman, 2002). However, as we aimed to supplement our results derived from OLS firm fixed effects regression with a count model, we decided to also run a random effects negative binomial regression to provide a more comprehensive empirical picture.

Second, a potential for reverse causality exists in the way that our dependent variables, digital patents and digital innovations, may affect the decision to conduct digital M&As. Similarly, a reverse relation may occur between digital patents and digital innovations. To mitigate potential biases from reverse causality, we lagged our independent variables for digital M&A and digital patents in our regressions.

Third, we faced a potential self-selection bias, as the decisions to undergo digital M&A and to build up digital knowledge are endogenous choices. An unobservable factor may thus drive the decision for digital M&A and to file new digital patents at the same time. A similar concern applied to the decision to build up digital knowledge and digital innovation. Hence, we followed a frequently applied approach (e.g., Busenbark et al., 2017; Saldanha et al., 2017; Stettner & Lavie, 2014) suggested by Shaver (1998), who proposed including a correction factor derived from a first-stage probit model estimating the likelihood to engage in the particular strategy in all second-stage regressions. We therefore estimated the probability to engage in digital M&A (in the most recent three years) and the probability to file digital patents (in the most recent three years) while accounting for our second-stage control variables and an exclusion criterion. The exclusion criterion should be correlated with the decision to engage in digital M&A (digital patents) but not correlated with the dependent variable (digital patents or digital innovations). As the exclusion criterion for digital M&A, we chose the average M&A activity in the industry over the previous three years (excluding the focal firm). We expected that an active M&A market increases the likelihood for M&A in general and thus also for digital M&A. At the same time, we did not expect that overall M&A activity would increase the focal firm's digital innovation outcomes.

For digital patents, we chose the host country's patent intensity (patent applications in the country by GDP), as we expected that firms in patent-intense countries were more likely to develop their own knowledge bases. We further expected that patent intensity within a country did not drive digital market offerings of the focal firms other than through its impact on digital patents. Finally, we used the predicted values of the probit regressions to calculate inverse Mills ratios (Heckman, 1979), which we incorporated as additional control variables in our firm fixed effects regressions.

These empirical considerations led to the following regression model to estimate H1 focusing on the relation between digital M&A and digital patents:

$$\begin{aligned} 3fy\ digital\ patents_{j,t} = \alpha &+ \beta_1(3ly\ digital\ M\ A)_{j,t-1} \\ &+ \gamma(controls)_{j,t-1} \\ &+ \beta_2(\lambda\ digital\ M\ A)_{j,t-1} + T_t \\ &+ fixed_j + \mu_{j,t} \end{aligned} \quad \text{(I)}$$

To investigate H2 focusing on the relation between digital patents and digital innovations, we employed the following regression model:

$$\begin{aligned} 3fy\ digital\ innovation_{j,t} = \alpha & \\ &+ \beta_1(3ly\ digital\ patents)_{j,t-1} \\ &+ \gamma(controls)_{j,t-1} \\ &+ \beta_2(\lambda\ digital\ patent)_{j,t-1} \\ &+ T_t + fixed_j + \mu_{j,t} \end{aligned} \quad \text{(II)}$$

In both equations t indexes time periods and j the firms. The items besides the dependent variables (*3fy digital patents* in equation I and *3fy digital innovation* in equation II), the independent variables *(3ly digital M&A* in equation I and *3ly digital patents* in equation II) and the control variables *(controls)* comprise the inverse Mills ratios controlling for the likelihood that a firm has engaged in digital M&A in the three most recent years *(λ digital M&A)* in equation I and the likelihood to engage in digital patents in the three most recent years (*λ digital patent*) in equation II, the intercept *(α)*, the time effects *(T)*, the firm-specific effect *(fixed)* only relevant for the fixed effects regression, and the error term *(μ)*.

To investigate the impact of digital M&A on digital innovation (H3a) and the proposed mediation effect of digital patents (H3b), we followed prior studies (e.g., Malhotra et al., 2018; Ndofor et al., 2011) and tested four conditions necessary for a mediation effect (Baron & Kenny, 1986): (1) digital M&A must significantly influence digital innovation; (2) digital M&A must significantly influence digital patents; (3) when both digital patents and digital M&A are included in a regression predicting digital innovation, the impact of digital patents needs to be significant; and (4) the effect of digital M&A should diminish in its significance and magnitude. Hence, we further ran a regression analysing the impact of digital M&A on digital innovation and a regression estimating digital innovation in which we included both digital patents and digital M&A. We also decided to employ a Sobel test (Sobel, 1982), which provides information on the significance and power of a mediation. Specifically, we tested the following models:

$$\begin{aligned} 3fy\ digital\ innovation_{j,t} = \alpha & \\ &+ \beta_1(3ly\ digital\ M\ As)_{j,t-2} \\ &+ \gamma(controls)_{j,t-1} \\ &+ \beta_2(\lambda\ digital\ M\ A)_{j,t-2} \\ &+ T_t + fixed_j + \mu_{j,t} \end{aligned} \quad \text{(III)}$$

$$\begin{aligned} 3fy\ digital\ innovation_{j,t} = \alpha & \\ &+ \beta_1(3ly\ digital\ M\ As)_{j,t-2} \\ &+ \beta_2(3ly\ digital\ patents)_{j,t-1} \\ &+ \gamma(controls)_{j,t-1} \\ &+ \beta_3(\lambda\ digital\ patents)_{j,t-1} \\ &+ \beta_4(\lambda\ digital\ M\&A)_{j,t-2} \\ &+ T_t + fixed_j + \mu_{j,t} \end{aligned} \quad \text{(IV)}$$

where t indexes time periods and j the firms. The items besides the dependent variable *(3fy digital innovation)*, the independent variable *(3ly digital M&A)*, the mediator variable *(3ly digital patents)* and the control variables (controls), comprise the inverse Mills ratio controlling for the likelihood to engage in digital M&A in the three most recent years (*λ digital M&A*) included in both equations and the inverse Mills ratio controlling for the likelihood to engage in digital patents in the three most recent years (*λ digital patent*) in equation IV, the intercept *(α)*, the time effects *(T)*, the firm-specific effect *(fixed)* only relevant for the fixed effects regression, and the error term *(μ)*.

4.2.6.2. Analysing the impact of digital innovation on firm performance (H4). To investigate the suggested impact of digital innovation on firm performance in H4, we used an OLS firm fixed effects regression because unobserved differences on the firm level could be major drivers of performance effects. Moreover, the firm fixed effects model helps to better isolate the effect of digital innovation on firm performance as it only estimates time-variant effects within a firm. For similar reasons, prior empirical studies aiming to draw conclusions on performance effects commonly employ firm fixed effects regressions (e.g., Litov et al., 2012; Müller et al., 2018; Pan et al., 2018). We again used lagged values of all our independent variables to mitigate potential biases from reverse causality. Specifically, we used the following model to analyse H4:

$$\begin{aligned} \textit{Firm performance}_{j,t+1} = \alpha & + \beta_1(\textit{3ly digital innovation})_{j,t} \\ & + \gamma(\textit{controls})_{j,t} + T_t + \textit{fixed}_j \\ & + \mu_{j,t} \end{aligned} \tag{V}$$

where t indexes time periods and j the firms. The items besides the dependent variable (*firm performance*), the independent variable (*3ly digital innovation*) and the control variables (*control*), comprise the intercept *(α)*, the time effects *(T)*, the firm-specific effect *(fixed)*, and the error term *(μ)*.

5. Results

5.1. Descriptive statistics

Table 2 displays the means, first and third quartile values, standard deviations, and pairwise correlations. The relatively low mean values of digital patents and innovation point to the difficulties physical product manufacturing industries face in building up digital knowledge and accomplishing digital innovation (Hylving et al., 2012). However, the standard deviations also indicate relatively large variations across firms. Due to partially strong correlations among some variables, we checked variance inflation factors (VIFs), which were below critical thresholds, indicating that our analysis is not constrained by multicollinearity (Wooldridge, 2002).

5.2. Building digital knowledge from digital M&A (H1)

Models 1 and 2 of Table 3 report the results of testing the impact of digital M&A on digital patents. In Model 1, we ran a firm fixed effects regression and observed a significant (p < .01), positive coefficient of our independent variable *3ly digital M&A*. In Model 2, we also found a significant (p < .01), positive coefficient of *3ly digital M&A* when running a random effects negative binomial regression. The results of Models 1 and 2 illustrate that digital M&A help file future digital patents and thus support H1.

5.3. Digital knowledge base and digital innovation (H2)

To test H2, we ran models with digital innovation as the dependent variable and preceding digital patents as the independent variable. In Model 3 of Table 3, we ran a firm fixed effects regression and found a significant (p < .001), positive coefficient of our independent variable *3ly digital patents*. The results

Table 2. Descriptive statistics and correlations.

No.	Variables	Mean	S.D.	Q1	Q3	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	3fy digital patents^{a} $_{(t)}$	2.93	7.52	0.00	2.00	1.00								
(2)	3fy digital patents^{b} $_{(t)}$	0.63	1.01	0.00	1.10	0.46	1.00							
(3)	3fy digital innovation^{a} $_{(t)}$	4.09	7.81	0.00	5.00	0.47	0.83	1.00						
(4)	3fy digital innovation^{b} $_{(t)}$	0.88	1.15	0.00	1.79	0.62	0.74	0.74	1.00					
(5)	3ly digital M&A $_{(t-1)}$	0.37	0.55	0.00	0.69	0.47	0.47	0.51	0.55	1.00				
(6)	3ly digital patents $_{(t-1)}$	0.39	0.74	0.00	0.51	0.51	0.49	0.58	0.60	0.84	1.00			
(7)	3ly M&A experience $_{(t-1)}$	1.49	1.03	0.69	2.20	0.10	0.11	0.10	0.06	−0.01	−0.01	1.00		
(8)	3ly digital alliances $_{(t-1)}$	0.36	0.48	0.00	1.00	0.27	0.17	0.19	0.22	0.10	0.14	0.57	1.00	
(9)	Entropy unrelated $_{(t-1)}$	0.34	0.39	0.00	0.51	−0.01	−0.01	0.06	0.01	−0.01	0.04	−0.01	0.18	1.00
(10)	Profit margin $_{(t-1)}$	4.62	3.25	2.22	7.02	−0.04	0.11	0.07	−0.05	0.02	−0.02	−0.05	−0.12	−0.06
(11)	capex $_{(t-1)}$	7.01	4.35	3.94	8.80	0.07	−0.03	−0.03	−0.03	−0.06	−0.03	0.05	0.05	0.06
(12)	R&D intensity $_{(t-1)}$	2.46	1.87	0.55	3.91	0.02	0.11	0.11	0.14	−0.03	−0.03	0.07	0.04	−0.17
(13)	Liquidity $_{(t-1)}$	8.94	7.75	4.10	10.85	0.05	−0.08	−0.12	−0.06	−0.05	−0.11	−0.15	−0.21	−0.19
(14)	Leverage $_{(t-1)}$	50.19	21.04	36.69	66.58	0.18	0.09	0.14	0.16	0.22	0.32	0.22	0.42	0.34
(15)	Capital intensity $_{(t-1)}$	4.71	0.84	4.32	5.26	0.31	0.17	0.23	0.17	0.15	0.22	0.16	0.13	0.11
(16)	Size $_{(t-1)}$	16.71	2.06	15.97	18.04	0.41	0.40	0.49	0.46	0.35	0.43	0.38	0.56	0.31
(17)	Sales growth $_{(t-1)}$	7.86	18.93	−3.93	17.14	0.06	−0.02	−0.09	−0.07	0.03	−0.03	−0.09	−0.12	−0.09
(18)	Industry growth $_{(t-1)}$	3.13	9.07	−1.76	11.64	−0.17	−0.10	−0.14	−0.19	−0.17	−0.23	−0.14	−0.28	−0.25
(19)	Market-to-book $_{(t-1)}$	0.46	0.45	0.22	0.53	−0.07	−0.01	−0.02	−0.17	0.03	−0.01	−0.12	−0.24	−0.24
(20)	Return on assets $_{(t-1)}$	4.01	3.44	1.95	5.59	0.15	0.45	0.50	0.36	0.26	0.32	0.05	0.27	0.00
(21)	3y EPS forecast $_{(t-1)}$	3.51	5.08	0.64	4.40	0.16	0.13	0.19	0.21	0.17	0.21	−0.14	−0.08	−0.03

No.	Variables	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(10)	Profit margin $_{(t-1)}$	1.00											
(11)	Capex $_{(t-1)}$	0.15	1.00										
(12)	R&D intensity $_{(t-1)}$	−0.05	0.00	1.00									
(13)	Liquidity $_{(t-1)}$	0.04	−0.06	−0.09	1.00								
(14)	Leverage $_{(t-1)}$	−0.23	0.07	0.08	−0.50	1.00							
(15)	Capital intensity $_{(t-1)}$	0.00	0.07	0.02	−0.19	0.31	1.00						
(16)	Size $_{(t-1)}$	−0.07	−0.01	0.29	−0.45	0.66	0.52	1.00					
(17)	Sales growth $_{(t-1)}$	0.26	−0.03	−0.25	0.19	−0.29	0.00	−0.23	1.00				
(18)	Industry growth $_{(t-1)}$	0.27	0.01	−0.19	0.34	−0.62	−0.27	−0.54	0.24	1.00			
(19)	Market-to-book $_{(t-1)}$	0.39	−0.03	−0.23	0.24	−0.40	−0.17	−0.37	0.33	0.55	1.00		
(20)	Return on Assets $_{(t-1)}$	0.10	−0.06	−0.10	−0.17	0.20	0.21	0.36	−0.04	−0.19	0.06	1.00	
(21)	3y EPS forecast $_{(t-1)}$	−0.03	−0.03	−0.04	0.12	−0.02	0.04	0.05	0.03	−0.06	0.12	0.10	1.00

N = 332; a: count variable; b: calculated as the natural logarithm of one plus the count variable. All values above 0.09 are significant at the 5% level

Table 3. Regression results (H1, H2 and H3).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Method:	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial
DV:	3fy digital patents $_{(t)}$		3fy digital innovation $_{(t)}$		3fy digital innovation $_{(t)}$		3fy digital innovation $_{(t)}$	
DV specified as:	Log	Count	Log	Count	Log	Count	Log	Count
3ly digital M&A $_{(t-1)}$	**0.792****	**1.069****						
	(0.004)	(0.001)						
3ly digital patents $_{(t-1)}$			**0.533*****	**0.433*****			**0.425*****	**0.350****
			(0.000)	(0.000)			(0.001)	(0.002)
3ly digital M&A $_{(t-2)}$					**0.717****	**0.945*****	**0.368***	**0.718****
					(0.001)	(0.000)	(0.042)	(0.005)
Controls								
3ly M&A experience $_{(t-1)}$	−0.181	−0.472**	−0.169	−0.320**	−0.206*	−0.364**	−0.154	−0.308**
	(0.137)	(0.002)	(0.096)	(0.007)	(0.046)	(0.002)	(0.107)	(0.007)
3ly digital alliances $_{(t-1)}$	0.096	−0.238	−0.051	−0.117	0.036	−0.161	0.007	−0.128
	(0.491)	(0.272)	(0.687)	(0.382)	(0.756)	(0.275)	(0.948)	(0.347)
Diversification $_{(t-1)}$	0.653	0.211	0.053	0.021	0.106	0.176	0.091	0.295
	(0.211)	(0.522)	(0.865)	(0.935)	(0.752)	(0.519)	(0.760)	(0.285)
Profit margin $_{(t-1)}$	0.038	0.042	0.007	−0.055*	0.014	−0.033	0.010	−0.066**
	(0.171)	(0.149)	(0.745)	(0.016)	(0.479)	(0.141)	(0.612)	(0.004)
Capex $_{(t-1)}$	−0.014	−0.004	0.017	−0.015	0.024	0.006	0.022	−0.005
	(0.563)	(0.881)	(0.226)	(0.502)	(0.181)	(0.799)	(0.154)	(0.824)
R&D intensity $_{(t-1)}$	−0.026	0.114	0.030	−0.103	0.015	−0.046	0.026	−0.141
	(0.678)	(0.222)	(0.519)	(0.259)	(0.763)	(0.629)	(0.595)	(0.127)
Liquidity $_{(t-1)}$	−0.008	−0.013	0.024*	0.005	0.013	0.001	0.017	−0.011
	(0.148)	(0.605)	(0.030)	(0.782)	(0.117)	(0.932)	(0.077)	(0.544)
Leverage $_{(t-1)}$	−0.009	−0.034***	−0.005	0.017*	−0.010	−0.003	−0.007	0.012
	(0.136)	(0.000)	(0.451)	(0.043)	(0.081)	(0.728)	(0.213)	(0.177)
Capital intensity $_{(t-1)}$	0.083	−0.076	0.037	−0.452*	−0.003	−0.464**	0.003	−0.564**
	(0.520)	(0.734)	(0.821)	(0.015)	(0.986)	(0.008)	(0.987)	(0.002)
Size $_{(t-1)}$	−0.282*	0.816**	−0.139	−0.172	−0.206	0.402*	−0.132	−0.181
	(0.034)	(0.005)	(0.347)	(0.468)	(0.081)	(0.031)	(0.368)	(0.431)
Sales growth $_{(t-1)}$	−0.003	−0.010	−0.001	0.006	−0.001	0.002	−0.001	0.007*
	(0.179)	(0.101)	(0.768)	(0.050)	(0.620)	(0.534)	(0.622)	(0.024)
Industry growth $_{(t-1)}$	−0.001	−0.005	0.003	0.012*	0.002	0.007	0.003	0.012*
	(0.704)	(0.583)	(0.289)	(0.048)	(0.455)	(0.276)	(0.288)	(0.043)
λ digital M&As $_{(t-1)}$	−0.119	−0.800**						
	(0.451)	(0.002)						
λ digital M&As $_{(t-2)}$					0.208	−0.129	0.194	0.117
					(0.178)	(0.509)	(0.249)	(0.546)
λ digital patents $_{(t-1)}$			−0.062	−1.098***			−0.04	−1.121***
			(0.497)	(0.000)			(0.694)	(0.000)
Constant	5.159*	−12.086**	2.635	6.771	3.704	−4.218	2.315	7.648
	(0.021)	(0.009)	(0.320)	(0.107)	(0.084)	(0.171)	(0.378)	(0.063)
Firm fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2/Chi2	0.38	153.9	0.57	344.6	0.55	315.0	0.58	344.7
N	332	332	332	332	332	332	332	332

***, **, and * indicate significance at the 0.1%, 1%, and 5% levels. One-tailed p-values are reported for our independent variables and two-tailed p-values for control variables. Standard errors are clustered at the firm level. Detailed information on all regression variables is provided in Appendix A1.

of the random effects negative binomial regression (Model 4 of Table 3) again display a significant ($p < .001$), positive effect of our independent variable *3ly digital patents*. Hence, the results support H2, suggesting that digital knowledge bases help OEMs drive digital innovation.

5.4. Direct and indirect effects of a digital M&A on digital innovation (H3a & H3b)

In H3a, we suggested that digital M&A has a positive effect on digital innovation, and in H3b we further predicted that this effect is partially mediated by digital patents. To test H3a, we tested the association between digital M&A and digital innovation in Models 5 to 8 in Table 3. Models 5 and 6 indicate a significant, positive impact of our independent variable *3ly digital M&As*. When we included digital patents as the mediator variable in the regressions (Models 7 and 8), we still found a significant, positive effect of our independent variable, *3ly digital M&As*. Hence, we found support for a direct effect of digital M&A on digital innovation, as suggested in H3a. To test if this effect was partially mediated by digital patents, we focused on the four conditions necessary for mediation (Baron & Kenny, 1986). Models 1 and 2 support the first condition by indicating a significant, positive impact of digital M&A on the mediation variable, digital patents. Models 5–8 support the second condition by indicating a significant, positive impact of digital M&A on digital innovation. Models 7 and 8 support the third condition by indicating a significant, positive effect of our independent variable, digital M&A, and also a significant, positive effect of our mediator variable, digital patents, when both variables are included in the same regression. Finally, consistent with the last condition necessary for a mediation, we observed in Models 7 and 8 that the effect of digital M&A diminishes in its significance and magnitude. Hence, all four conditions for a (partial) mediation effect by digital patents are present.

In addition to the four conditions of Baron and Kenny (1986), we also ran a Sobel test (Sobel, 1982), presented in Table 4. The results of this test indicate a significant ($p < 0.05$) mediation effect of digital patents on the association between digital M&A and digital innovation. In addition, we calculated the effect ratios to indicate the strength of the mediation effect (Ndofor et al., 2011). The effect ratios support a strong but partial mediation effect (Jose, 2013). In sum, our analyses supported H3b, suggesting that digital patents partially mediate the relationship between digital M&A and digital innovation.

5.5. Performance implications of digital innovations (H4)

To test H4, we estimated the impact of digital innovation on operating performance (i.e., return on assets) in Model 9, on market performance (i.e., market-to-book ratio) in Model 10, and on analyst forecasts (i.e., three-year EPS forecasts) in Model 11. Table 5 presents the results of these regressions. All models indicate a significant, positive impact of digital innovations on the OEMs' performances. The results suggest that digital innovation significantly increases both the operating and capital market performance of OEMs. The significant impact on analysts' forecasts further supports the idea that digital innovation is crucial for an OEM's future success. Therefore, our results support H4.

5.6. Robustness of results

In addition to our main results, we also ran various robustness tests (untabulated). First, we tested alternative specifications of control variables and obtained similar results. Second, we restricted our three-year dependent variables to only one year, yielding similar results. Moreover, we employed alternative lead–lag specifications to test the mediation effect and found consistent support for a mediation. Finally, we included digital M&A and digital patents in the performance regression and still found support for a significant, positive effect of digital innovation on firm performance.

5.7. Additional analysis – relatedness of acquired and created digital knowledge

While our main analysis indicated that digital M&A increase the digital knowledge base of the acquirer, it is also interesting to further explore this process. In particular, the question remains whether digital M&A are associated with, first, knowledge creation closely related to the knowledge of the target and/or, second, new knowledge creation that is unrelated to the previous knowledge of the target. Hence, to investigate if digital patents by the acquirer are related to the knowledge bases of the targets, we ran an additional analysis. Following previous studies (e.g., Grimpe & Hussinger, 2014; Makri et al., 2010), we compared the International Patent Classification (IPC) codes of all patents filed by a *target* in the time *before* the M&A with the IPC codes of patents filed by the *acquirer after* the M&A. Based on this comparison, we differentiated the acquirer's digital patents filed after the M&A in those that were related to the target's patents and those that were unrelated. We focused on three degrees of relatedness (same IPC class, same IPC subclass, and same IPC code) and, for each degree, constructed variables for related patents and unrelated patents filed by the acquirer. We then used these variables to estimate the influence of digital M&A on related and unrelated patents filed by the acquirer. Table A3 of Appendix A2 displays the results of these analyses. The results indicate that digital M&A significantly drive both related and unrelated knowledge creation on the part of the acquirer.

6. Discussion and conclusions

While more and more traditional firms turn to M&A to support their digital innovation endeavours (Boote et al., 2019; Malette & Goddard, 2018), a gap exists between the practical relevance and academic understanding of digital M&A in such contexts (Henningsson et al., 2018). Therefore, we investigate the influence of digital M&A on the digital knowledge base of the acquirer

Table 4. Mediation effect.

MV: *3y digital patents* IV: *3y digital M&A*	c (IV-DV)	a (IV-MV)	SEa	b (MV-DV)	SEb	Z-value of Sobel test[1]	Effect ratio[2]
DV: 3fy digital innovation (Firm fixed effects)	0.717	0.792	0.271	0.425	0.116	2.285*	0.469
DV: 3fy digital innovation (Negative binomial)	0.945	1.069	0.326	0.350	0.119	2.190*	0.396

DV = Dependent variable; MV = Mediator variable; IV = Independent variable; c = coefficient for the association between the IV and DV; a = coefficient for the association between the IV and the MV; SEa = standard error relating to the coefficient for the association between the IV and the MV; b = coefficient for the association between the MV and the DV while including the IV; SEb = standard error relating to the coefficient for the association between the MV and the DV while including the IV; * = $p < 0.05$ (two-tailed); 1 = $Z = a*b/((b^2*SEa^2 + a^2*SEb^2)^{0.5})$ (see, Baron & Kenny, 1986); 2 = Effect ratio = a * b/c

Table 5. Regression results (H3).

	Model 9	Model 10	Model 11
Method	Firm fixed effects	Firm fixed effects	Firm fixed effects
Dependent variable	Market-to-book $_{(t+1)}$	Return on assets $_{(t+1)}$	3y EPS forecast $_{(t+1)}$
3ly digital innovation $_{(t)}$	**0.044***	**1.136****	**1.983***
	(0.049)	(0.002)	(0.012)
Controls			
Diversification $_{(t)}$	−0.071	1.054	2.345
	(0.276)	(0.340)	(0.083)
Profit margin $_{(t)}$	0.010	0.154	0.285*
	(0.125)	(0.098)	(0.029)
Capex $_{(t)}$	−0.010*	−0.129**	−0.122**
	(0.027)	(0.009)	(0.001)
R&D intensity $_{(t)}$	−0.036*	0.242	0.557
	(0.048)	(0.348)	(0.149)
Liquidity $_{(t)}$	−0.009	0.048	−0.006
	(0.089)	(0.286)	(0.744)
Leverage $_{(t)}$	0.001	0.059**	0.031
	(0.089)	(0.001)	(0.167)
Capital intensity $_{(t)}$	−0.059*	−1.458*	−0.227
	(0.033)	(0.037)	(0.663)
Size $_{(t)}$	−0.172***	−0.290	0.042
	(0.000)	(0.193)	(0.916)
Sales growth $_{(t)}$	0.000	0.008	−0.01
	(0.851)	(0.449)	(0.278)
Industry growth $_{(t)}$	0.003	−0.013	0.013
	(0.052)	(0.201)	(0.332)
Constant	3.807***	10.304**	−1.792
	(0.000)	(0.006)	(0.810)
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adjusted R2	0.25	0.15	0.32
N	337	337	314

***, **, and * indicate significance at the 0.1%, 1%, and 5% levels. One-tailed *p*-values are reported for our independent variables and two-tailed *p*-values for control variables. Standard errors are heteroscedasticity-consistent and clustered at the firm level. Detailed information on all regression variables is provided in Appendix A1.

as well as the consequences for digital innovation and firm performance. Our findings suggest that executing digital M&A helps companies to build their digital knowledge base, which enables them to drive digital innovation that in turn improves firm performance.

Our study contributes to IS research on M&A (e.g., Benitez et al., 2018). While the majority of work has investigated contexts where IS represented a byproduct of the M&A, a more recent stream focuses on M&A where IS are central to the acquirers rational behind the deal. We contend that, as opposed to other technological acquisitions, the particular characteristics of digital technologies – such as reprogrammability, data homogenisation, and self-reference (Y. Yoo et al., 2010) – influence the reusability of the acquired components across contexts, driving potential for recombinations of underlying knowledge and, thus, knowledge creation (Fleming, 2001). While knowledge-building from acquisitions has been generally investigated with regard to organisational knowledge (as opposed to technical knowledge) (Henningsson, 2015) and with regard to technical knowledge in IT industries (Datta & Roumani, 2015), the increasingly relevant context of digital knowledge building via M&A by traditional firms is to date missing. We complement existing literature on M&A for the inherent value of IS with an emphasis on industrial-age contexts by theorising and empirically demonstrating that industrial-age incumbents can effectively build their digital knowledge base by conducting digital M&A.

Furthermore, our study contributes to research on digital innovation in industrial-age contexts. While prior work has revealed that industrial-age incumbents face substantial capability gaps when embracing digital innovation (Svahn et al., 2017), systematic investigations of potential countermeasures are missing. Our work indicates that conducting digital M&A contributes to closing capability gaps by contributing to building the digital knowledge base of the acquirer. We provide empirical evidence for the conceptually described importance of knowledge and learning as drivers of digital innovation capabilities (Kohli & Melville, 2018) as well as the value of building digital knowledge on the part of industrial-age incumbents albeit the distributed nature of digital innovation (Y. Yoo et al., 2012). Finally, we provide evidence for the positive performance implications of digital innovation even in traditional contexts, a claim unsupported by empirical evidence so far. In what follows, we discuss the implications of our work.

6.1. Building and utilising a digital knowledge base for digital innovation

Developing digital knowledge is challenging for industrial-age incumbents (e.g., Piccinini et al., 2015), leading them to search for external sources (Svahn et al., 2017). Owing to the comprehensive access to digital materiality that they grant for the acquirer, digital M&A may have specific advantages as compared to other forms of external knowledge acquisition. The nature of digital technologies invites experimentation and allows for adaptations that may ease knowledge utilisation and combination (Y. Yoo et al., 2012). The aforementioned effects are unlikely to occur only via hiring digital talent without having digital technologies in place. Furthermore, these effects are likely bigger the less restricted access to technology is, which might render M&A superior to strategic alliances. This particularly holds true in the context of digital innovation, where the development of products and services building upon digital technologies represents the core target (Nambisan et al., 2017). Owing to the distance between the knowledge involved (Yoo et al., 2012, 2010), our findings contrast with much prior work that did not find positive impacts of distant knowledge acquisitions on acquirers (e.g., Ahuja & Katila, 2001; Makri et al., 2010). While past studies have investigated a variety of human, organisational, and interorganisational measures that might help to improve in this regard (e.g., Graebner, 2004; Graebner et al., 2010), our findings indicate the special role that digital materiality (Yoo et al., 2012) could play in the post-M&A outcomes of the acquirer. While the underlying knowledge might be distant from that of the acquirer, the dynamic and malleable nature of digital technologies makes it more accessible and adaptable so that it can be utilised for combinations across contexts. In this regard, digital M&A can be seen as distinct compared to other types of acquisitions, allowing also distant acquirers to profit.

Apart from the positive impacts that digital M&A might have, not all challenges in developing digital knowledge can be alleviated. Indeed, it is very likely that acquisitions are complemented and influenced by various internal measures such as reorganisations or new innovation practices (Svahn et al., 2017). It might also be the case that firms that conduct digital M&A are particularly aware of the potential difficulties that may emerge after the acquisition and therefore employ special measures in preparation and profit from them. For example, they may deploy special councils where people involved in the acquisition come together, share ideas and discuss upcoming issues (e.g., Henningsson et al., 2016). We see such activities as complementary to our explanations related to digital M&A. In the spirit of IS research in the field of organisational inertia (Besson & Rowe, 2012), we think that knowledge stickiness post M&A has multiple dimensions including socio-cognitive aspects that can be addressed by aforementioned organisational measures and socio-technical aspects that are also influenced by the flexibility of the respective resources. Accordingly, while there might be other effects at play as well, we claim that there are particular effects that are related to the digital materiality involved. These effects indeed may very likely work together to build knowledge as digital technologies acquired can serve as adaptable boundary objects that drive collaboration and knowledge exchange complementary to other organisational measures such as councils or new innovation units.

A digital knowledge base is of particular value in driving digital innovation (Kohli & Melville, 2018). While this holds true across contexts, it receives a special meaning in industrial-age contexts. The nature of digital innovation has been portrayed as distributed and researchers have explicitly and implicitly pointed to the value of complementarities (e.g., Yoo et al., 2012). However, in digital innovation, where physical and digital components are combined, achieving this complementarity is much harder than in digital industries (Piccinini et al., 2015; Yoo et al., 2010). While industrial-age incumbents presumably possess knowledge pertaining to the physical device layer, they need to, first, enable leveraging this knowledge inside a modular layered architecture by embedding digital into physical materiality (Yoo et al., 2012) and, second, assure that it is complemented by knowledge pertaining to the network, service, and content layers (Y. Yoo et al., 2010) to remain relevant in digital business environments. Building an internal digital knowledge base can therefore have an amplifying effect on the value of established competences (Spender, 1996) and open up new innovation opportunities. For example, automotive OEMs build upon digital knowledge to develop connected car solutions that serve a vibrant ecosystem of partners for digital innovation (Henfridsson & Yoo, 2014). Importantly, sustaining such digital innovation capabilities requires constant learning efforts (Kohli & Melville, 2018). As digital technologies and related knowledge evolve at high speed and quickly become obsolete, nurturing and replenishing the knowledge base is a continuous task (Yoo et al., 2012) and helps to become more receptive to new digital knowledge (Cloodt et al., 2006). As knowledge is only temporarily combined in digital innovation, the knowledge base can be applied repeatedly for new and diverse combinations, thus triggering further convergent and generative digital innovations (Nambisan et al., 2017) and serving as a platform for new product/market combinations (Kogut & Zander, 1992; Yoo et al., 2012).

6.2. Acquiring for inherent value in industrial-age contexts and IS integration

Prior works on IS in M&A have mostly focused on IS integration in contexts of instrumental IS value. The context of digital M&A and digital innovation, in turn, where the value of IT becomes inherent and digitalised customer demand creates pressures for synergy realisation, gives also IS integration a new key target: building knowledge for innovative solutions (Datta &

Roumani, 2015). Prior literature has convincingly established the role of IS integration to enable post-M&A knowledge exchange and creation (e.g., Benitez et al., 2018; Gao & Iyer, 2006). Accordingly, IS integration might be influential to the knowledge effects that we theorise as well as investigate here, and our empirical evidence shows that acquirers are, on average, successful in this regard. From this perspective, our results extend prior work in three ways.

First, we argue that the characteristics of digital technologies help to access the knowledge that motivated the deal by mobilising knowledge exchange. Our additional analysis indicates that digital knowledge related to the knowledge brought in by the target is developed after the M&A. While Du (2015) emphasised the ability to redeploy IS resources by the acquirer and Benitez et al. (2018) focus the flexibility of the acquirer's IT infrastructure, both driving post-M&A performance, our perspective highlights the value of the flexibility of the acquired digital materiality, which might help to adapt acquired components to the circumstances of the acquirer. Through this flexibility in IS integration, transferring the desired knowledge can be achieved by mitigating problems of context specificity and stickiness (Graebner, 2004).

Second, we know from Busquets (2015) that, contingent on the capabilities of the acquirer, surprising synergies and new knowledge creation can happen in the course of IS integration as firms learn and discover new variations while re-configuring assets and resources post M&A. Our findings support this view and provide complementary explanations. The additional analysis revealed that new digital knowledge unrelated to the knowledge brought in by the target is developed after the M&A. We argue that in the case of digital M&A, due to the dynamic and malleable nature of digital technologies and the generativity they induce (Yoo et al., 2012), experimentation and improvisation, key to creating variations in the interaction of organisations and technology post M&A (Busquets, 2015), are particularly fostered, for instance, by the ability to alter established or add new functional applications. Furthermore, due to the malleability of digital technologies and the decontextualization they induce, a high amount and variety of interactions might be provided, creating ample options for exploration (Kallinikos et al., 2013). Through triggering discoveries in the course of IS integration, digital M&A may lead to serendipitous value by fostering the discovery of new knowledge (Graebner, 2004).

Third, we know from prior works that the integration of particular digital M&A might be very challenging or even detrimental (Datta & Roumani, 2015), potentially requiring boundary-spanning activities and structures between target and acquirer (Henningsson et al., 2016). However, the direct effect of digital M&A on digital innovation we found indicates that the components acquired by digital M&A can sometimes be directly applied for digital innovation. A potential explanation could be that, in particular cases, firms may have built flexible IS infrastructures (Benitez et al., 2018) represented, for example, in digital service platforms, which enable firms to directly profit from the acquired components (e.g., modules for the platform). In these cases, the need for deep integration might be relatively low owing to the loose coupling of the modular layered product architecture (Yoo et al., 2010). However, in sum our findings suggest that digital innovation is fostered through the effects on the digital knowledge base of the acquirer. We argue that the latter is particularly relevant for digital M&A and digital innovation in industrial-age contexts. Existing work following the contextual stream pertaining to the inherent value of IS in M&A has focused on digital industry contexts (Datta & Roumani, 2015), investigating how acquirers utilise a particular technology or solution developed by targets. From a knowledge-based view, this perspective relates to acquiring knowledge for replication purposes (Majchrzak et al., 2004), an important perspective, particularly in digital industries, where digital M&A can quickly deliver complements to the existing digital knowledge base of the acquirer (Gao & Iyer, 2006). The context of industrial-age incumbents acquiring digital targets, in turn, renders a further perspective relevant. In this context, companies have to combine digital and physical knowledge to innovate (Yoo et al., 2012), potentially precluding them from immediately replicating the digital knowledge. The rationale might thus not be to utilise a particular piece of knowledge but to create new knowledge. This perspective relates to acquiring knowledge for innovation purposes (Majchrzak et al., 2004) and represents a valuable extension of our understanding as digital M&A contexts diversify by emphasising learning effects that may occur beyond a particular deal (Vermeulen & Barkema, 2001).

6.3. Limitations and future research

Our study has some limitations that need to be highlighted. Restricting our sample to the automotive industry limits the generalisability of our findings. Furthermore, in our argumentation, we have assumed that industrial-age incumbents have conducted digital M&A to utilise the knowledge of the target. The findings of our additional analysis support this thinking and indicate that the acquisitions are not only conducted to foreclose (Shenoy, 2012) knowledge from the public to defend established market positions. However, indeed, there might be other motivations. For instance, perhaps targets are acquired for the pre-emptive value of their patents and to secure the advantages of the internal developments of the acquirer in a similar area of expertise (Grimpe & Hussinger, 2014). Future work should therefore delve more into the different motivations of conducting digital M&A as well as their consequences. Similarly, although we believe in the robustness of our findings over time (see also next section), we call for future work to replicate our findings when new generations of digital technologies have emerged and digital innovation capabilities of industrial incumbents have improved.

Apart from that, while we are among the first to employ digital-related proxies in an archival study, these measures come also with certain drawbacks. In this research, the digital knowledge base holds a central position. In our argumentation and operationalisation, we used digital patents filed as a proxy. In doing so, on the one hand, we purposefully deviate from studies that have used patents as proxies for final innovation outcomes (e.g., Saldanha et al., 2017). We agree with Ahuja and Katila (2001) that patents as "are best regarded as intermediate outcomes between acquisitions and value creation" (p. 217). On the other hand, with our approach, we follow studies that viewed new patents filed as extensions of the firms' knowledge base (e.g., Prabhu et al., 2005). While patents were often applied as an indicator for knowledge, knowledge goes beyond what is and can be patented. For instance, tacit knowledge held by individuals is usually not subject to patenting processes, yet is of particular importance in a firm's innovation activities (e.g., Cloodt et al., 2006). We assume that after a digital M&A is executed, also such tacit knowledge is built, for instance, as employees of the acquirer experiment with new digital technologies (Svahn et al., 2017). Such knowledge outcomes are hard to measure in an empirical study. Therefore, we decided for patents as an observable and established indicator but view it as a proxy for the broader concept of the digital knowledge base involving articulated and tacit types of knowledge (Vermeulen & Barkema, 2001). However, while this assumption should particularly hold true in patent-intensive industries such as automotive or manufacturing in general (e.g., Saldanha et al., 2017), the transferability of our operationalisation of a digital knowledge base is limited when it comes to industries where the patenting rate is very low such as the financial, insurance or real estate industry (e.g., Galasso & Simcoe, 2011). Moreover, we have to acknowledge that our measure of digital innovations relies on announcements by the firms' press departments. Hence, it may be possible that firms over- or under-report their digital innovation outcomes. With regard to the latter, although there exist broader conceptualisations of digital innovation that also include process innovations alongside new services and products (e.g., Kohli & Melville, 2018), we purposefully opted for a conceptualisation and measurement that focuses on market offerings (Nambisan et al., 2017) for two particular reasons. First, as suggested by recent case studies (Svahn et al., 2017), we think that actually bringing digital products and services to the market is both a current necessity (e.g., Gregory et al., 2018; Lyytinen et al., 2016) and a very challenging task for industrial-age incumbents as to new organising logics and product architectures involved (Yoo et al., 2010). Second, as compared to internal process innovation, new market offerings are more reliably publicly published, observable from the outside and thus represent a measurable indicator (Prabhu et al., 2005). Thus, our focus on press releases should be limited to conceptualising digital innovation with regard to market offerings (Nambisan et al., 2017) as firms may be less inclined to disclose digital enabled process innovation.

Finally, interesting fields of work for future research also arise from the particular research model we selected for our empirical investigation. On the basis of our research focus, we systematically derived specific areas and research questions for future work on digital M&A that would complement and challenge our study (see Table 6).

We focused on the basic effect of digital M&A on an acquirer's digital knowledge base, which should be further explored in the future. For instance, investigating differential effects of particular types of digital knowledge (e.g., pertaining to different layers of the modular layered architecture), seems very promising and would extend works that have proceeded similarly in IT industries (Gao & Iyer, 2006). Furthermore, while our results indicate that digital M&A help to build a digital knowledge base, future research could delve deeper into the characteristics of incumbent firms to examine what factors enable more or less effective digital M&A. Moreover, the deeper dimensions and processes of knowledge integration in these contexts remain unclear owing to the large-scale quantitative character of our study. In particular, specific organisational measures (such as boundary spanning structures or having a chief digital officer in place) might positively moderate the relations we established in this study. More in-depth qualitative studies might provide promising insights. Furthermore, future studies should investigate potential drawbacks of conducting digital M&A, particularly as to whether it substitutes or complements alternative and especially internal ways of building digital knowledge. The link between digital innovation and firm performance also needs additional work. As we have described, in the context of industrial-age incumbents, several performance effects emerge (e.g., securing device pricing and creating multiple new revenue streams varying in pricing mode) that call for further differentiation and empirical investigation.

Table 6. Future research opportunities.

Area	Research questions
Digital M&A	• Which antecedents and consequences of different motivations for conducting digital M&A can be discerned? • What makes incumbent firms particularly effective in building knowledge from digital M&A (e.g., with regard to organisational structures and capabilities)? • How can digital M&A be differentiated (e.g., with regards to the kind of knowledge involved)? • How do mechanisms to achieve IS integration interact with mechanisms to achieve digital knowledge creation?
Building a Digital Knowledge Base	• What is the relationship between digital talent acquisition and new digital patents filed by the recruiting firm? • What is the relationship between measures of reorganising (e.g., new digital structural units or appointments of a chief digital officer) and new digital patents filed by incumbent firms? • How effective are different mechanisms for building a digital knowledge base and how do these mechanisms interact?
Leveraging Digital Knowledge for Digital Innovation	• How do different types of digital knowledge (e.g., generic vs. specific) influence digital innovation? • What strategies in knowledge application in terms of the ration of the size of internal and external knowledge bases can be discerned and what is their impact on digital innovation? • What is the role of digital platforms in leveraging digital knowledge for digital innovation?
Performance Impact of Digital Innovation	• What is the relationship between different types of digital innovation (e.g., process vs. product vs. business model) on firm performance? • How does the selection of pricing models for particular services (e.g., ongoing subscription vs. one-time feature or device sale) influence the impact of digital innovation on firm performance?

6.4. Managerial implications

Our study has valuable implications for business practice, particularly for managers in industrial-age industries. Our study provides evidence that managers can increase their firms' digital innovativeness by building a digital knowledge base and should thus proactively search for ways to enable digital knowledge creation. While building a digital knowledge base might be achieved by several measures, our findings indicate that conducting digital M&A is a viable strategy. However, managers should be aware that digital M&A may differ from M&A that their firms may have previously conducted, particularly in relation to IS integration. Moreover, while M&A might have a direct effect on digital innovation because, for example, acquired applications can be easily coupled with a firm's existing platform, it is likely that digital M&A influence digital innovation by influencing the digital knowledge base of the acquirer. In evaluating digital M&A, managers should therefore pay attention to the learning effects, not just the particular application of what has been acquired. Owing to the fast-paced and continuous nature of digital innovation, integrating knowledge might be more valuable than the particular application.

Apart from that, while digital transformation is a necessity, our work suggests that managers in industrial-firms should be sensitive to their particular contextual circumstances. Accordingly, our findings should not be understood as indicating that building a digital knowledge base is a one-time effort that established firms need to invest to transition from physical to digital. First, while we witness digitalisation in more and more contexts, as far as the eye can see, physical materiality and related knowledge will remain relevant also in contexts such as the Internet-of-Things. Second, although digital M&A foster the building of a digital knowledge base, the latter needs continuous further impulses as technological evolution progresses. For instance, when learning about cloud computing or big data analytics via digital M&A, a firm may face new gaps in emerging technological paradigms such as distributed ledger technologies or 3D-printing. Although the knowledge acquired through digital M&A is not bound to its particular use case and may have a general effect on understanding digital technologies, it does not automatically cover new technological paradigms, which we will encounter more frequently as digitalisation progresses. In sum, the "going-in-position" of industrial players, the need to combine digital and physical, which differs from purely digital players, will most likely endure. Therefore, the relations we theorise and empirically demonstrate in this study may have value going beyond a current phase of digital transformation.

Finally, some managers in industrial-age industries might still question the relevance and impact of digital innovation in their sector. Our findings about the performance impacts of digital innovations may enrich their thinking by emphasising the value both in relation to current and future performance.

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Appendices

Appendix A1: *Data sources and variable descriptions*

Table A1. Data, definition, operationalisation, and calculation of main variables.

Variable	Definition	Operationalisation	Calculation	Data Source
3fy digital patents	Patents of a firm in a given three-year period that intensely leverage digital technologies and were filed originally by the acquirer. Digital technologies are defined as combinations of information, computing, communication, and connectivity technologies and include instances such as cloud computing, mobile technology, social media, and big data analytics (Bharadwaj et al., 2013).	Manual evaluation of whether a patent matches the definition of digital patents based on patent information retrieved form Espacenet. Digital patents are then assigned to a particular year based on their filing date.	Calculated as the natural logarithm of one plus the number of digital patent application by a firm in the current and the next two years and also used as pure count for robustness. The variable captures the time frame from 2000 to 2016. However, as the variable considers three years (e.g., in 2014, the years 2014, 2015, and 2016), data availability is restricted to the period between 2000 and 2014.	Espacenet
3fy digital	innovations	Creations of or changes to market offerings that result from the use of digital technologies for a firm in a given three-year period. Digital technologies are defined as combinations of information, computing, communication, and connectivity technologies and include instances such as cloud computing, mobile technology, social media, and big data analytics (Bharadwaj et al., 2013).	Manual evaluation of whether a press release matches the definition of digital innovations. Press releases were obtained from LexisNexis.	
Calculated as the natural	logarithm of one plus the number of number digitally related changes in the firm's market offerings in the current and the next two years and also used as pure count for robustness. The variable captures the time frame from 2000 to 2016. However, as the variable considers three years (e.g., in 2014, the years 2014, 2015, and 2016) data availability is restricted to the period between 2000 and 2014.	LexisNexis		
3ly digital M&A	Mergers and acquisitions by a firm in the last three years that aim at acquiring (or merging with) firms that intensely leverage digital technologies as critical elements of their business models (Tumbas et al., 2017; Huang et al., 2017). Digital technologies are defined as combinations of information, computing, communication, and connectivity technologies and include instances such as cloud computing, mobile technology, social media, and big data analytics (Bharadwaj et al., 2013).	Manual evaluation of whether an M&A matches the digital M&A definition based on all the M&A of our sample in the SDC databank.	Calculated as the natural logarithm of one plus the number of digital M&A conducted in the three most recent years. As we lagged our variable 3ly digital M&A by either one or two years, the variable 3ly digital M&A$_{t-1}$ covers the time frame from 1997 to 2013 and the variable 3ly digital M&A$_{t-2}$ the time frame from 1996 to 2012.	SDC
databank				
3ly digital patents	Patents of a firm in a given three-year period that intensely leverage digital technologies and were originally filed by the acquirer. Digital technologies are defined as combinations of information, computing, communication, and connectivity technologies and include instances such as cloud computing, mobile technology, social media, and big data analytics (Bharadwaj et al., 2013).	Manual evaluation of whether a patent matches the definition of digital patents based on patent information retrieved form Espacenet. Digital patents are then assigned to a particular year based on their filing date.	Calculated as the natural logarithm of one plus the number of digital patent applications by a firm in the three most recent years. The variable captures the time frame from 1997 to 2013, as the variable is lagged by one year in our regression models.	Espacenet

Appendix A2: *Additional Analysis*

Table A2. Data sources and descriptions for firm performance and control variables.

Variable	Description & Calculation	Data Source
Firm performance variables		
Return on assets	Calculated as net operating profit divided by the average of last year's and current year's total assets. Measured in percent.	Thomson Reuters Datastream
Market-to-book ratio	Variable is measured as the OEMs market capitalisation divided by total assets.	Thomson Reuters Datastream
3-year EPS forecasts	Consensus of the analysts' 3-year earnings per share (EPS) forecast. EPS indicates a company's profitability in terms of a firm's net profit relative to one share of common stock.	IBES databank
Control variables		
3ly M&A experience	Natural logarithm of one plus the number of non-digital M&As in the recent three years.	SDC databank
3ly digital alliances	Dummy variable that indicates whether a firm has started to engage in digital alliance in the three most recent years. Digital alliances were coded similar to digital M&As as strategic alliances and joint ventures that aim at cooperating with firms that intensely leverage digital technologies as critical elements of their business models.	SDC databank
Size	Natural logarithm of firm's net sales.	Thomson Reuters Datastream
Leverage	Ratio of total debt divided by total assets. Measured in percent.	Thomson Reuters Datastream
Profit margin	Measured as operating profit margin, which equals to operating income divided by net sales. Measured in percent.	Thomson Reuters Datastream
Sales growth	One-year growth of a firm's net sales in percent.	Thomson Reuters Datastream
Liquidity	Calculated as cash divided by total asset. Measured in percent.	Thomson Reuters Datastream
R&D intensity	Ratio of R&D spending divided by net sales. Measured in percent.	Thomson Reuters Datastream
Diversification	Measured as entropy index that accounts for unrelated sales diversification. We only considered segments that are unrelated from the firm's primary segment.	Thomson Reuters Datastream
Capex	Calculated as capital expenditures divided by net sales. Measured in percent.	Thomson Reuters Datastream
Capital intensity	Natural logarithm of one plus the ratio between property, plant, and equipment and the number of employees.	Thomson Reuters Datastream
λ digital M&As	Inverse Mills-ratio derived from a probit regression estimating the likelihood to engage in digital M&A in the three most recent years. The inverse Mills-ratio is then calculated as the probability density function to the cumulative density function for engaging in digital M&A.	Own calculation
λ digital patents	Inverse Mills-ratio derived from a probit regression estimating the likelihood to engage in digital patents the three most recent years. The inverse Mills-ratio is then calculated as the probability density function to the cumulative density function for engaging in digital patents.	Own calculation
Industry growth	One-year sales growth of the automotive industry in percent.	Thomson Reuters Datastream

Table A3. Influence of digital M&A on related and unrelated digital patents.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Method:	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial	Firm fixed effects	Negative binomial
(Un-)Relatedness:	Same IPC class		Different IPC class		Same IPC subclass		Different IPC subclass		Same IPC (full)		Different IPC (full)	
DV:	3fy related digital patents $_{(t)}$		3fy unrelated digital patents $_{(t)}$		3fy related digital patents $_{(t)}$		3fy unrelated digital patents $_{(t)}$		3fy related digital patents $_{(t)}$		3fy unrelated digital patents $_{(t)}$	
3ly digital M&A $_{(t-1)}$	**0.334****	**2.686*****	**0.771****	**1.712*****	**0.262***	**1.957***	**0.804****	**2.026*****	**0.171***	**1.912***	**0.802****	**1.877*****
	(0.008)	(0.000)	(0.004)	(0.000)	(0.010)	(0.029)	(0.004)	(0.000)	(0.028)	(0.042)	(0.003)	(0.000)
Controls												
3ly M&A experience $_{(t-1)}$	−0.036	−0.635	−0.184	−0.425*	−0.063	−0.902	−0.182	−0.387*	−0.081	−0.922	−0.171	−0.342*
	(0.753)	(0.233)	(0.064)	(0.014)	(0.522)	(0.203)	(0.094)	(0.022)	(0.343)	(0.141)	(0.127)	(0.043)
3ly digital alliances $_{(t-1)}$	0.066	−1.518*	0.024	−0.343	0.064	−2.039**	0.029	−0.416	0.043	−2.219**	0.034	−0.418
	(0.560)	(0.018)	(0.856)	(0.134)	(0.517)	(0.002)	(0.828)	(0.063)	(0.593)	(0.003)	(0.797)	(0.060)
Diversification $_{(t-1)}$	0.185	−0.663	0.389	−0.231	0.164	−0.904	0.392	−0.117	0.170	−0.833	0.395	−0.129
	(0.633)	(0.470)	(0.298)	(0.495)	(0.626)	(0.227)	(0.341)	(0.717)	(0.493)	(0.521)	(0.357)	(0.684)
Profit margin $_{(t-1)}$	0.041	0.300***	0.031	0.091**	0.039	0.317***	0.034	0.089**	0.021	0.917***	0.041	0.100***
	(0.088)	(0.000)	(0.185)	(0.002)	(0.074)	(0.000)	(0.172)	(0.001)	(0.127)	0.000	(0.121)	(0.000)
Capex $_{(t-1)}$	0.009	−0.027	−0.006	0.015	0.003	−0.143	−0.003	0.028	0.009	−0.562**	−0.006	0.031
	(0.522)	(0.744)	(0.758)	(0.585)	(0.751)	(0.146)	(0.894)	(0.300)	(0.269)	(0.001)	(0.781)	(0.240)
R&D intensity $_{(t-1)}$	−0.010	−0.614	−0.016	0.133	−0.005	−0.583	−0.023	0.065	−0.025	−0.629*	−0.015	0.046
	(0.751)	(0.084)	(0.693)	(0.240)	(0.867)	(0.110)	(0.597)	(0.575)	(0.275)	(0.013)	(0.743)	(0.693)
Liquidity $_{(t-1)}$	−0.003	0.024	−0.005	0.057*	−0.002	0.110	−0.006	0.044	−0.002	−0.003	−0.006	0.048*
	(0.282)	(0.746)	(0.239)	(0.029)	(0.418)	(0.134)	(0.205)	(0.073)	(0.364)	(0.973)	(0.211)	(0.046)
Leverage $_{(t-1)}$	0.001	−0.087**	−0.003	−0.003	0.000	−0.120***	−0.003	−0.012	0.000	−0.033	−0.003	−0.021
	(0.887)	(0.007)	(0.509)	(0.826)	(0.908)	(0.000)	(0.586)	(0.306)	(0.976)	(0.198)	(0.607)	(0.059)
Capital intensity $_{(t-1)}$	−0.054	−0.809*	0.037	−0.156	−0.039	−0.302	0.028	−0.154	0.047	−1.607*	0.020	−0.101
	(0.537)	(0.042)	(0.777)	(0.489)	(0.602)	(0.502)	(0.836)	(0.464)	(0.262)	(0.028)	(0.880)	(0.621)
Size $_{(t-1)}$	−0.055	3.726**	−0.224	0.522	−0.072	4.546***	−0.217	0.578*	−0.091	5.017***	−0.213	0.711*
	(0.528)	(0.002)	(0.071)	(0.069)	(0.321)	(0.000)	(0.073)	(0.042)	(0.144)	(0.000)	(0.079)	(0.013)
Sales growth $_{(t-1)}$	0.001	−0.010	−0.002	−0.015*	0.001	−0.011	−0.002	−0.013*	0.001	−0.036	−0.002	−0.015*
	(0.643)	(0.507)	(0.140)	(0.028)	(0.719)	(0.450)	(0.198)	(0.035)	(0.665)	(0.194)	(0.213)	(0.020)
Industry growth $_{(t-1)}$	−0.003	−0.103***	−0.001	0.002	−0.002	−0.119***	−0.002	−0.003	−0.001	−0.148**	−0.002	−0.006
	(0.467)	(0.001)	(0.745)	(0.825)	(0.596)	(0.000)	(0.528)	(0.772)	(0.406)	(0.008)	(0.480)	(0.499)
λ digital M&As $_{(t-1)}$	0.050	−0.255	−0.015	−0.788*	−0.018	−1.665*	0.023	−0.692*	−0.033	−1.575	0.024	−0.626*
	(0.625)	(0.693)	(0.904)	(0.012)	(0.835)	(0.027)	(0.846)	(0.018)	(0.662)	(0.194)	(0.839)	(0.028)
constant	0.823	−58.597**	3.968*	−9.333	1.219	−72.058***	3.788	−9.769*	1.288	−82.344***	3.733	−11.965*
	(0.553)	(0.003)	(0.049)	(0.056)	(0.285)	(0.000)	(0.054)	(0.043)	(0.185)	(0.001)	(0.057)	(0.013)
Firm fixed effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2/Chi2	0.10	56.7	0.35	152.5	0.10	58.0	0.36	164.3	0.09	30.6	0.36	166.4
N	332	332	332	332	332	332	332	332	332	332	332	332

In this analysis, we estimated the influence of digital M&A on related as well as unrelated digital patents filed by the acquirer after the transaction. We therefore compared the patents of the targets filed prior to the acquisition with thepatents filed by the acquirer after the transaction. We distinguished between related and unrelated patents by comparing the International Patent Classifications (IPCs) of the patents. We focused on three degrees of relatedness and, foreach degree, constructed a variable for related and unrelated patents. First, we classified patents as related if they were in the same IPC class (3-digit) (see Models 1–4); second, we classified patents as related if they were in the same IPCsubclass (4-digit) (see Models 5–8); finally, we only considered patents related if they exhibited exact matches of the full IPC (i.e., subgroup-level) (see Models 9–12). Moreover, we restricted the comparison to patents filed by the acquirer in the three years after thetransaction. However, when considering all future patents filed by the acquirer, we obtained similar results.

***, **, and * indicate significance at the 0.1%, 1%, and 5% levels, respectively. One-tailed *p*-values are reported for our independent variables and two-tailed *p*-values for control variables. Standard errors are clustered at the firm level. Detailed information on all control variables is provided in Appendix A1.